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S-RAD Model Overview

Safety & Insurance | July 2018

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Summary

To support Uber's company-wide priority to reduce critical safety incidents, the Safety & Insurance team has developed a data-driven intervention for preventing sexual assaults. The intervention -- called **Safety Risk Assessed Dispatch (S-RAD)** -- consists of two components:

- Machine learning models that assess the safety risks associated with all potential driver-rider matches at the point of dispatch.
- A down-ranking procedure that incorporates safety risk scores when selecting the optimal driver for dispatch (subject to marketplace constraints).

Evidence suggests **this approach may be able to prevent up to 15% of sexual assaults in the US by down-ranking 1% of the highest risk trips.** The following sections elaborate on the intervention strategy and the performance of the v1 model:

1. [Overview](#)
2. [Methodology](#)
3. [Model Performance](#)
4. [Most Important Features](#)
5. [Shadow Mode Results](#)
6. [Implementation Plan](#)
7. [Team](#)

[Appendix A: Descriptive Statistics](#)

[Appendix B: Variable List + Definitions](#)

[Appendix C: Evaluation Plan](#)

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1. Overview [\[back to top\]](#)

Sexual assaults¹ are one of the most tragic and infuriating forms of interpersonal conflicts that could occur on the Uber platform. To protect our users from these crimes, the Safety & Insurance team has developed a data-driven intervention that uses machine learning to score the safety risks associated with all potential driver-rider matches at the point of dispatch. The team proposes to use these scores to down-rank² high-risk matches subject to a set of marketplace constraints to minimize the risk of sexual assaults.

The motivating insight behind this intervention -- called **Safety Risk Assessed Dispatch (S-RAD)** -- is that many sexual assaults have correlates and precursors that may enable Uber to better anticipate them, and hence, prevent them by implementing well-designed safety products. For example, in the US, sexual misconduct and sexual assaults are disproportionately more likely to occur on:

- Trips that occur late night and on the weekends.
- Trips that originate from a bar area.
- Trips with a driver and rider of different genders.

**See descriptive statistics in [Appendix A: Descriptive Statistics](#).*

This report provides evidence that by leveraging these types of signals, **it may be possible to predict 15% of sexual assaults that occur on the Uber platform in the US by flagging 1% of the highest risk trips** (evidence from v1 model applied to historical out-of-sample test set). [Figure 1](#) depicts the percent of sexual assaults that can be correctly predicted (recall) for every incremental increase in the percent of trips flagged.

Prediction, however, does not equal prevention. The actions and interventions triggered by the model predictions need to change real-world outcomes. The down-ranking strategy proposed here may not have any impact in supply-constrained markets where alternative matches do not exist. And even where there is a surplus of supply, down-ranking may not be sufficient to keep predators from eventually exploiting the platform. Finally, it may not be possible to implement model-based interventions without generating prohibitive costs on the marketplace, such as

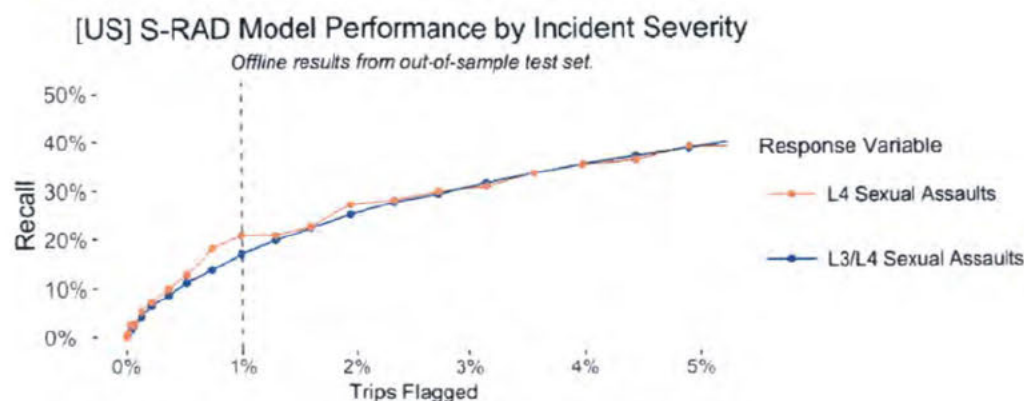
¹ 'Sexual assaults' are defined here as any kind of non-consensual touching or intercourse, and indecent exposure. [Table 1](#) provides incident types according to Safety & Insurance's incident taxonomy.

² 'Down-ranking' is a marketplace intervention in which a particular driver-rider pair that is considered for dispatch is given an MGCV (Market Generated Value) cost such that the dispatch is considered less valuable than other non-down-ranked alternative matches considered when optimizing matches across a market. Within the current dispatch framework, down-ranking is effectively blocking the pair unless there are no alternative pairs available (a.k.a., "soft filter").

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undermining the ability of drivers and riders to use the platform at specific times or locations, or if they belong to a particular gender.

Figure 1



Notes: US P2P trips (including Pool) between March 1 - May 31, 2018 (100% of positives, 1% sample of negatives). Recall for all sexual assaults with both driver + rider reporters (source: JIRA). 3358 L3/L4 incidents and 110 L4 incidents in test set. Results from Female Model V1 RC 26 and Male Model V1 RC 22.

Randomized experiments will ultimately be necessary to answer these questions in a compelling way. But to demonstrate that S-RAD is viable and experiments can be conducted with minimal legal and marketplace risks, **S-RAD was deployed into shadow mode in Los Angeles on April 20, 2018**. Starting on this day, all driver-rider pairings considered for dispatch for Los Angeles UberX trip requests were scored for their safety risks in near real-time (but not actioned on). The results suggest that S-RAD is a viable strategy for prevention. More specifically, during the shadow period (April 20 - June 12):

- S-RAD correctly anticipated **15% of sexual assaults** occurring on Los Angeles UberX trips (13/85) at the 1% trip trigger rate. This included **38% of L4 sexual assaults** (3/8).
- 99% of trips flagged by the model (at the 1% trip trigger rate) had an alternative driver-rider match that passed the model check (i.e., scored under risk threshold).
- Female and male drivers are not flagged at a different rate.

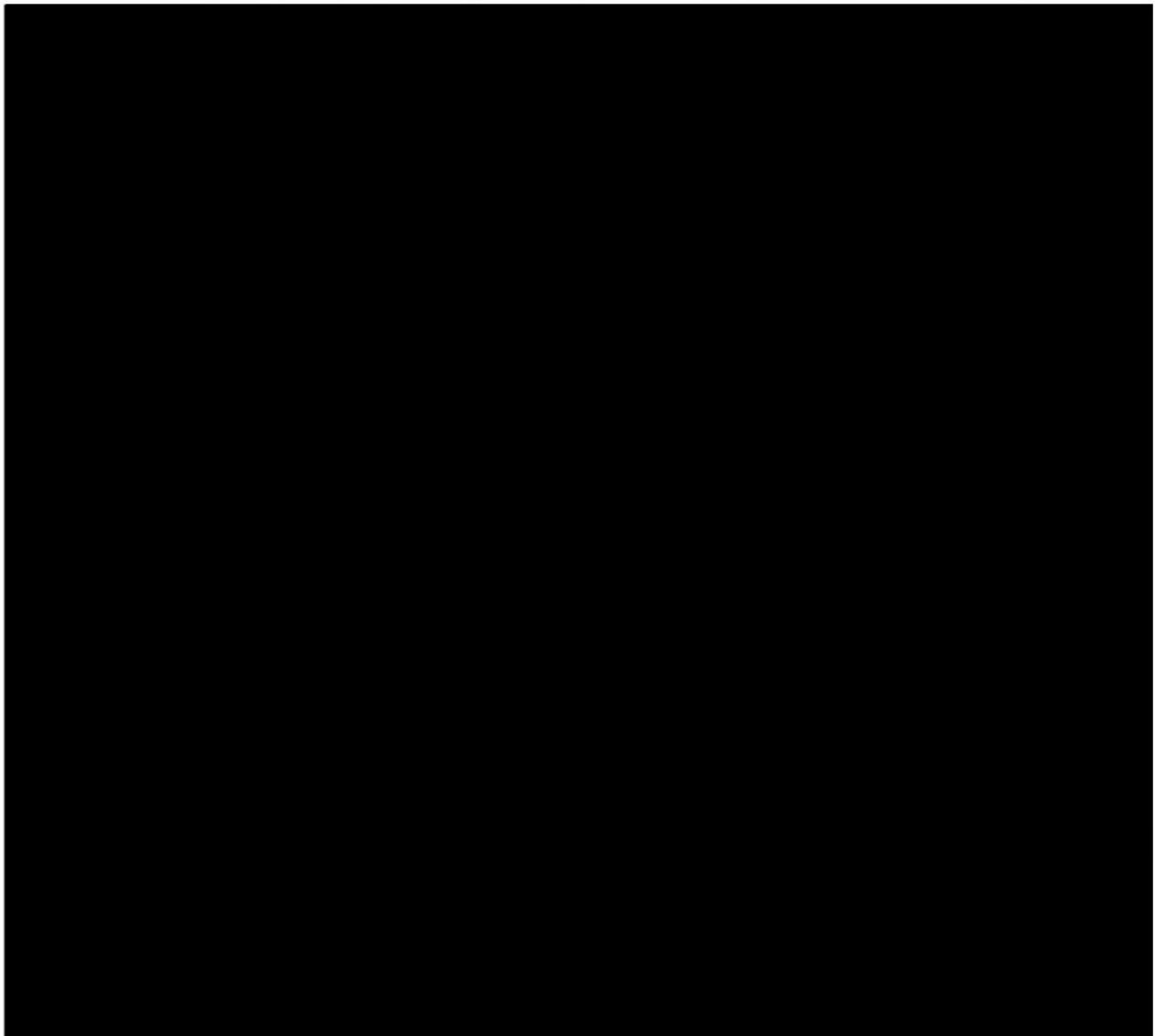
*Full results available in [Section 5: Shadow Mode Results](#).

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The sections below elaborate on [the methodology](#), [the performance of the v1 model](#), [the most important predictors](#), [results from shadow mode in Los Angeles](#), and [the proposed implementation plan](#), which involves a series of randomized evaluations consisting of a limited pilot, a within-city switchback, and a multi-city experiment (pending discussions with Operations, Marketplace, Legal). Positive findings from these experiments -- from safety, marketplace, and legal perspectives -- are a requirement for scaling.

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The S-RAD model consists of two gender-specific models trained to predict sexual assaults at the driver-rider dyad level. More details:



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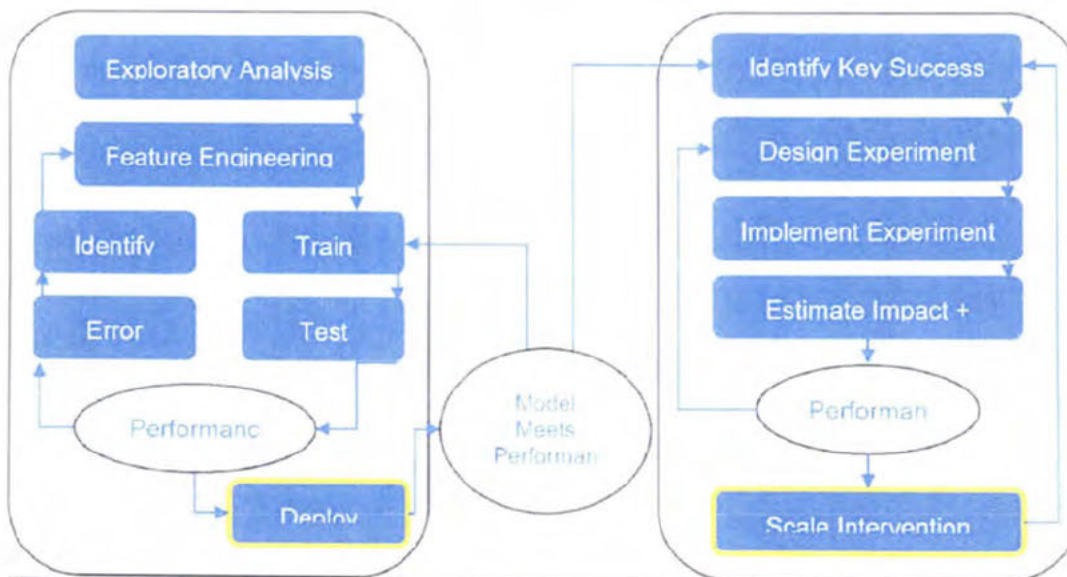
- Over 200 features considered. Final models include <40 features, which have been tailored to optimize predictive performance by driver gender.

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Table 1: Sexual Assaults and Sexual Misconduct Incident Types

Sexual Assault	Sexual Misconduct	
Physical - Attempted / Accidental Touching	Staring or Leering	Verbal - Non-explicit Inappropriate Remark / Gesture
Physical - Forced or Sexual Touching	Verbal - Explicit Inappropriate Remark / Gesture	Verbal - Non-explicit Inappropriate Remark / Gesture - comments on appearance
Physical - Masturbation / Indecent Exposure	Verbal - Explicit Inappropriate Remark / Gesture - comments on appearance	Verbal - Non-explicit Inappropriate Remark / Gesture - flirting
Physical - Non-Consensual Sexual Intercourse	Verbal - Explicit Inappropriate Remark / Gesture - flirting	Verbal - Non-explicit Inappropriate Remark / Gesture - personal questions
	Verbal - Explicit Inappropriate Remark / Gesture - personal questions	Verbal - Non-explicit Inappropriate Remark / Gesture - soliciting more contact
	Verbal - Explicit Inappropriate Remark / Gesture - soliciting more contact	Verbal - Threat of Sexual Assault

Figure 2: Framework for Model Development, Testing, and Iteration



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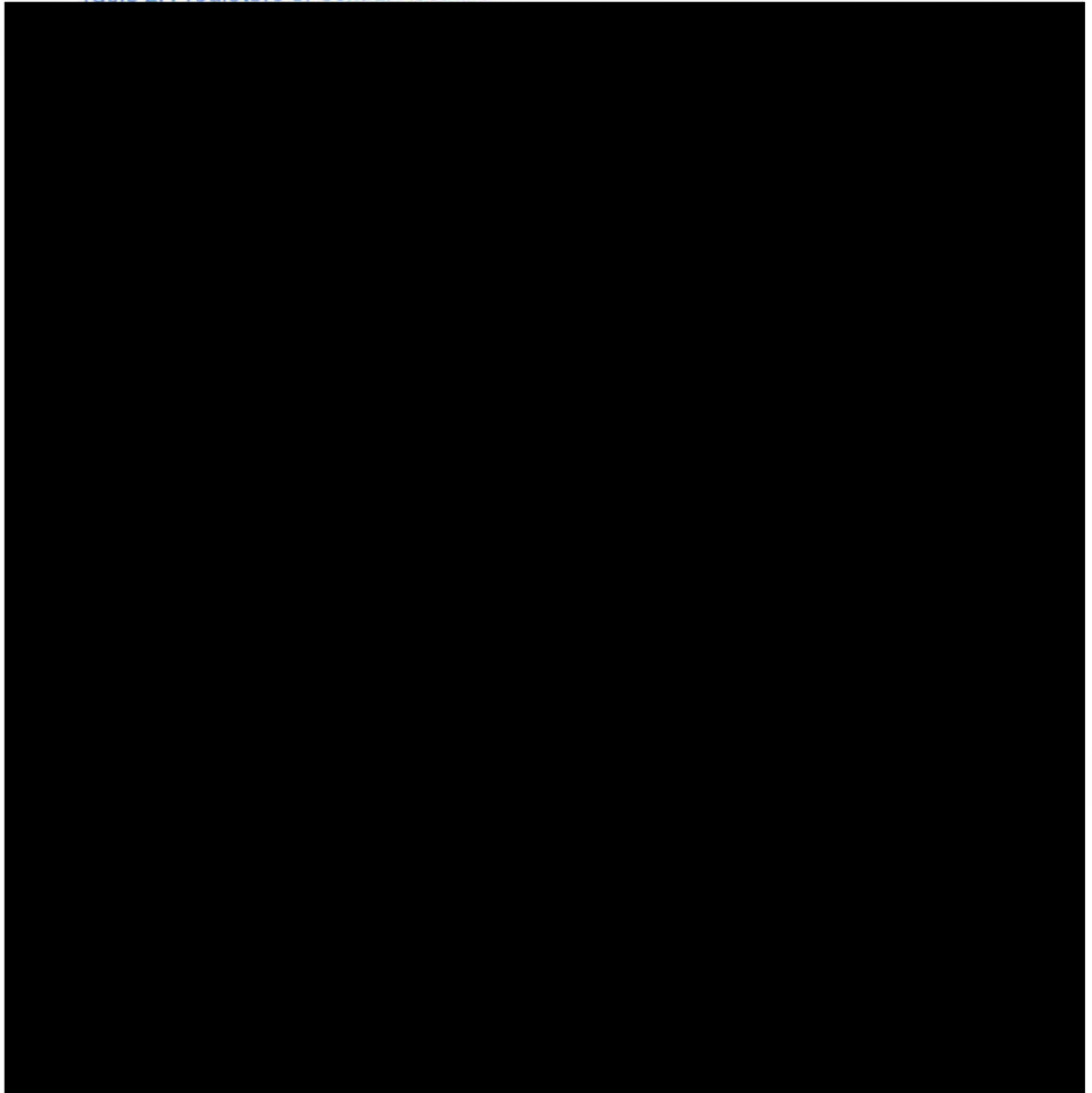
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Table 2: Predictors of Sexual Assaults



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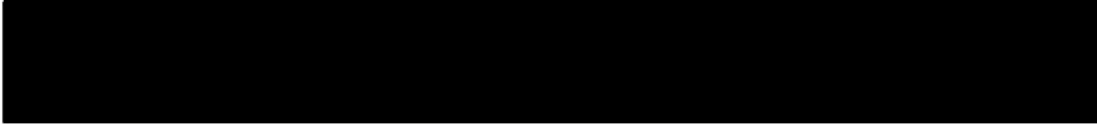
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3. Model Performance [\[back to top\]](#)

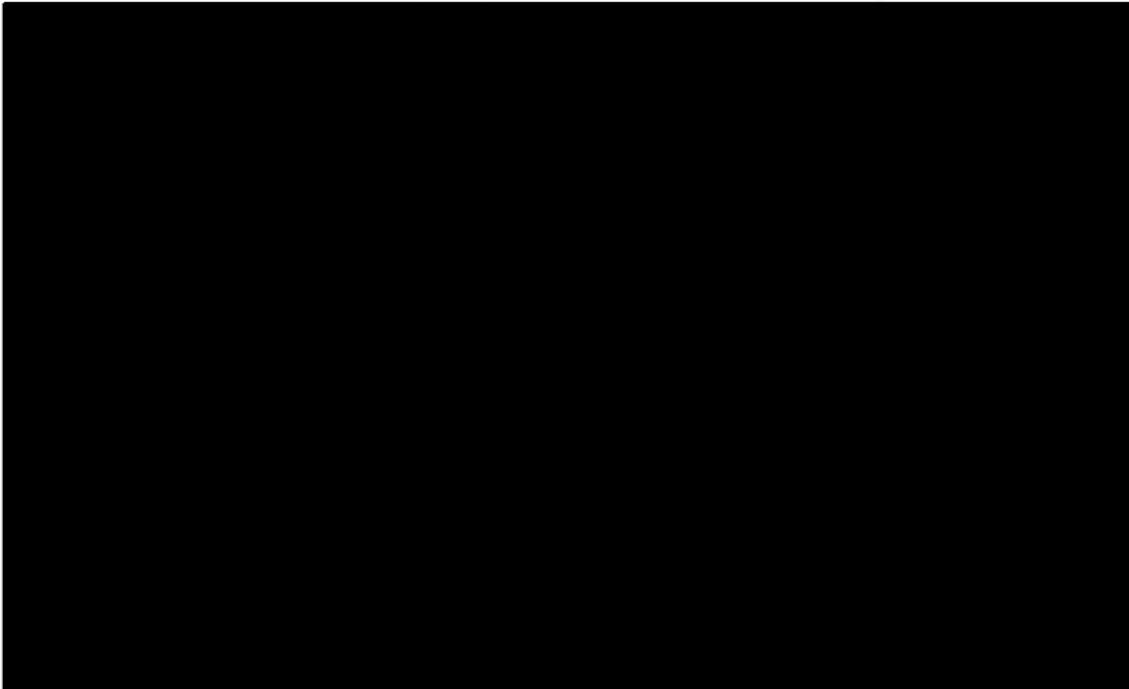
The accuracy of the S-RAD model is assessed on two primary metrics:



The goal is to maximize **recall** (predictive performance) subject to a constraint or “budget”, which is defined here as the **trip trigger rate** (*threshold to be selected with stakeholders*). All recall and trigger rate metrics are computed on an out-of-sample test set that is never analyzed before generating model predictions.

Over 50 models were tested to select the v1 S-RAD model presented in this report, with each model differing on at least one of the following dimensions: feature set, hyperparameters, training labels, down-sampling ratio, and training set time period.

The best performing v1 model is able to achieve **>15% recall on sexual assaults at the 1% trip trigger rate** in out-of-sample test sets. The v1 model has the following attributes:



One of the advantages of this machine learning-based approach is the ability to tune the model to catch more incidents by flagging more trips (but at the cost of more false positives), or to reduce business impact by flagging only the trips where there is high confidence it is high risk.

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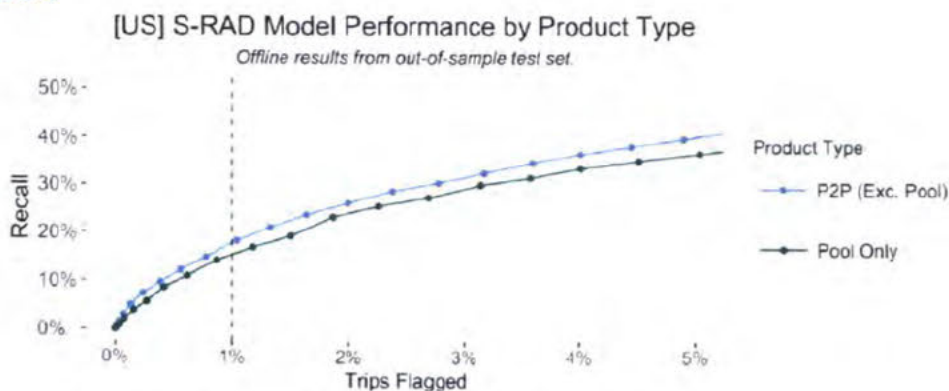
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Figure 3 shows this relationship by plotting recall as a function of trip trigger rate. The figure further breaks-down performance by P2P excluding Pool versus Pool only to shed more light on model performance. In some respects, incidents on Pool may be more difficult to anticipate because the model is trained to assess risk at the driver-rider level and not the rider-rider level. Indeed, results indicate that the model is better at predicting incidents on non-Pool P2P trips, but the difference is marginal (18% recall v. 15% recall at 1% trip trigger rate in out-of-sample test set).

Results also reveal that predictive performance is stronger for sexual assaults involving female drivers compared to male drivers (see Figure 4). In the majority of cases involving female drivers, the female driver is the alleged victim and the alleged offender is the rider. The recall-trigger rate curve in Figure 5 shows that the female driver model is able to achieve >20% recall on these types of incidents with a rider alleged offender (534 cases on P2P excluding Pool, 83 on Pool in test set). The model performs substantially worse for incidents involving a female driver alleged offender (likely due to small sample size; 34 cases on P2P excluding Pool, 9 on Pool in test set).

For sexual assaults involving male drivers, the male driver is more often than not the alleged offender. Figure 6 shows the model is marginally better at predicting these incidents where the alleged offender is the male driver (522 cases on P2P excluding Pool, 273 on Pool) rather than the rider (951 cases on P2P excluding Pool, 368 on Pool), but the difference is small.

Figure 3



Notes: US P2P trips between March 1 - May 31, 2018 (100% of positives, 1% sample of negatives). Recall for all sexual assaults with both driver + rider reporters (source: JIRA). 2482 incidents on P2P (exc. Pool), 864 incidents on Pool. Results from Female Model V1 RC 26 and Male Model V1 RC 22.

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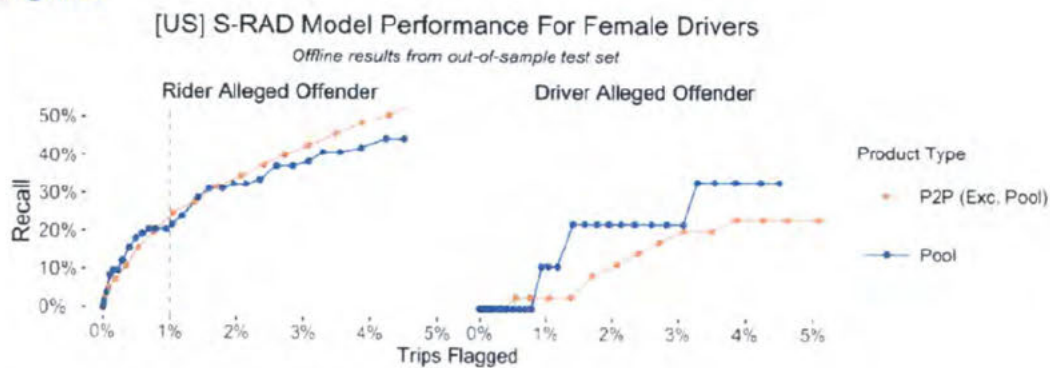
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Figure 4



Notes: US P2P trips (exc. Pool) between March 1 - May 31, 2018 (100% of positives, 1% sample of negatives). Recall for all sexual assaults with both driver + rider reporters (source: JIRA). Female Drivers: 733 incidents on P2P (Exc. Pool); Male Drivers: 1749 incidents on P2P (Exc. Pool). Results from Female Model V1 RC 26 and Male Model V1 RC 22.

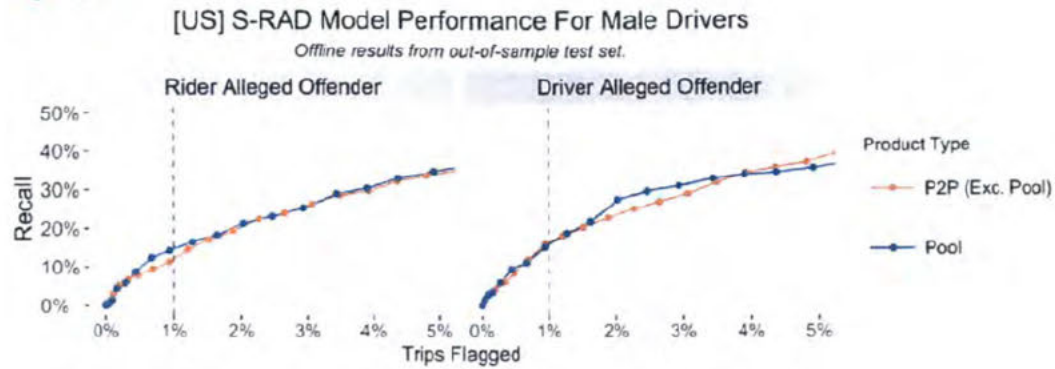
Figure 5



Notes: US P2P trips between March 1 - May 31, 2018 (100% of positives, 1% sample of negatives). Recall for all sexual assaults with both driver + rider reporters (source: JIRA). Rider Alleged Offender: 534 incidents on P2P (Exc. Pool); 83 incidents on Pool. Driver Alleged Offender: 34 incidents on P2P (Exc. Pool); 9 incidents on Pool. Results from Female Model V1 RC 26 and Male Model V1 RC 22.

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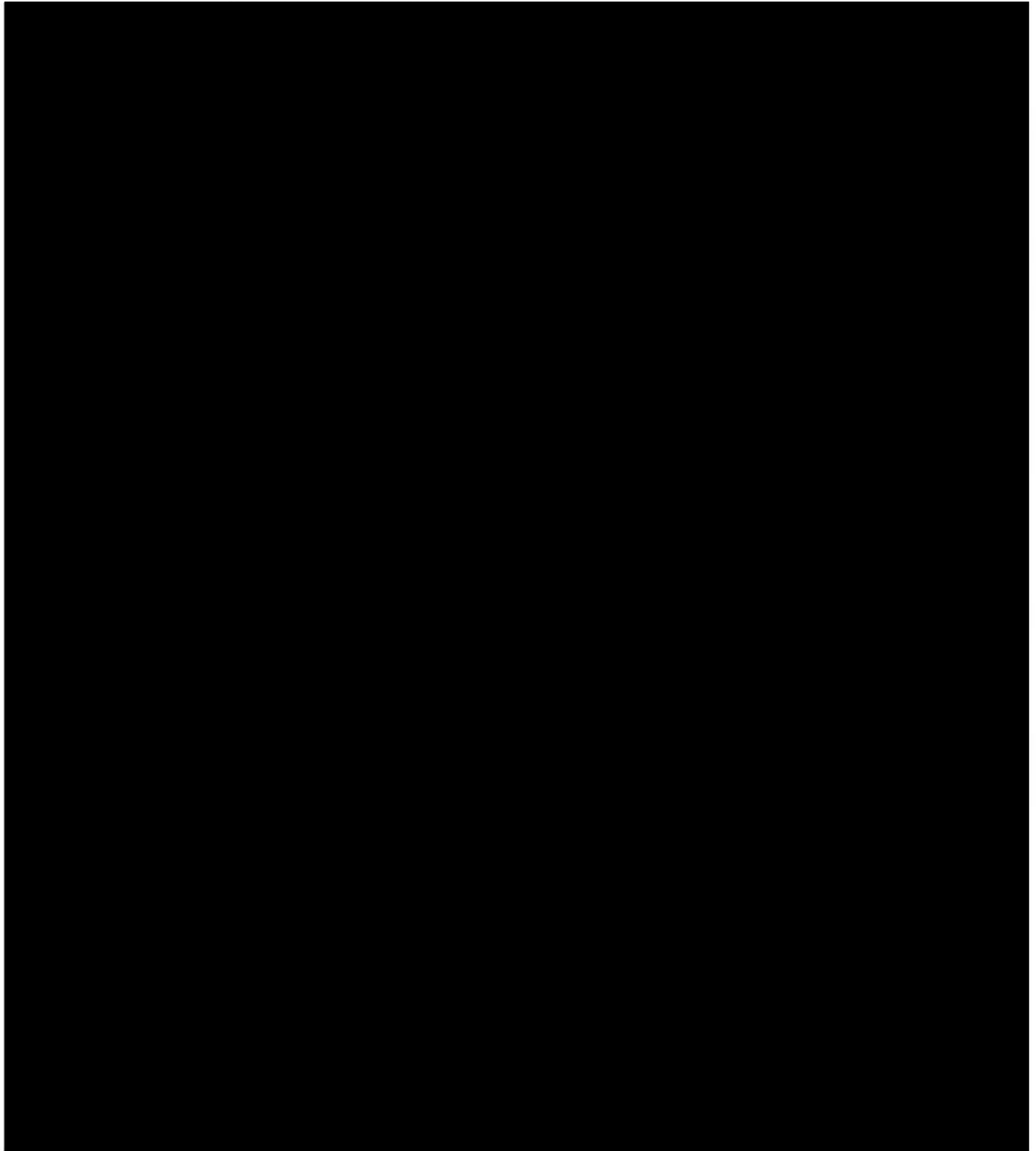
Figure 6



Notes: US P2P trips between March 1 - May 31, 2018 (100% of positives, 1% sample of negatives). Recall for all sexual assaults with both driver + rider reporters (source: JIRA). Rider Alleged Offender: 522 incidents on P2P (Exc. Pool); 273 incidents on Pool. Driver Alleged Offender: 951 incidents on P2P (Exc. Pool); 368 incidents on Pool. Results from Female Model V1 RC 26 and Male Model V1 RC 22.

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4. Most Important Predictors [\[back to top\]](#)



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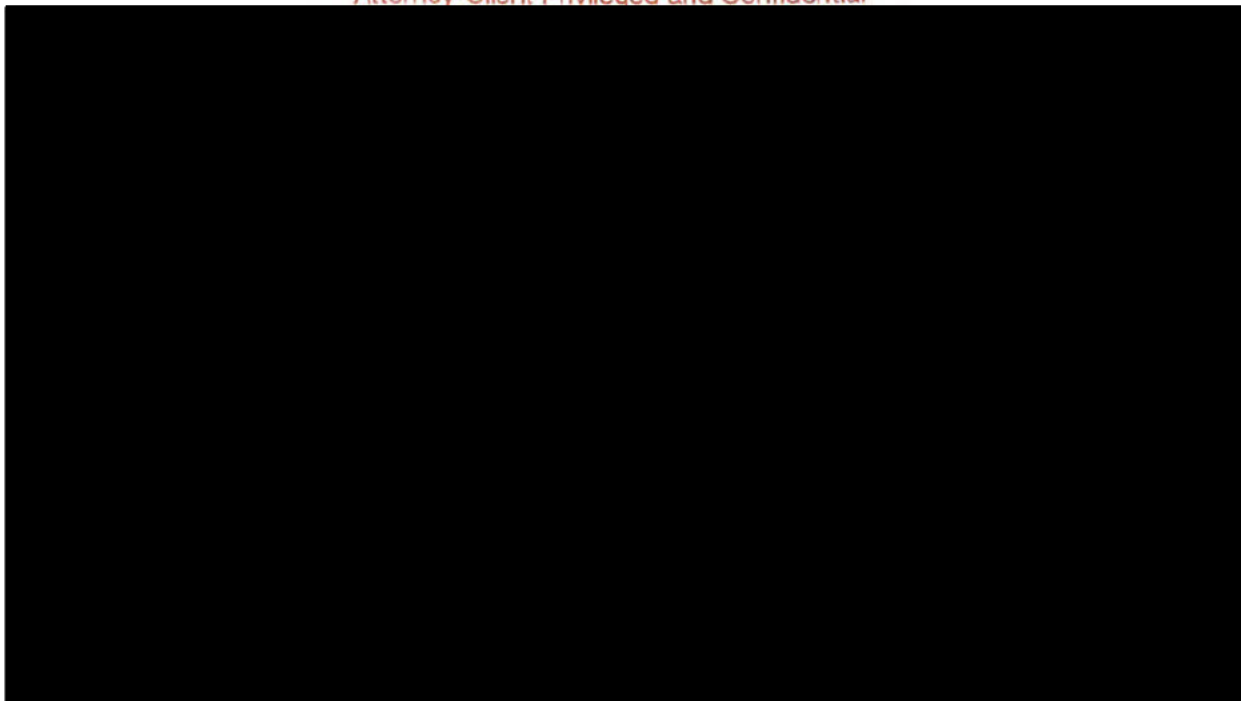


Table 3: Variable Importance Ranks by Feature Bundle and Model Type

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5. Shadow Model Results (Los Angeles) [\[back to top\]](#)

As a first step towards demonstrating that S-RAD can prevent sexual assaults within marketplace constraints, S-RAD was deployed in shadow mode on April 20, 2018. Starting on this day, all driver-rider pairings considered for dispatch for Los Angeles UberX trip requests were scored for their safety risks in near-real time (but not actioned on). On average, there were 175k jobs per day and 8M driver-rider pairings considered for dispatch per day.

Results provide evidence that S-RAD is a viable strategy for prevention. More specifically, during the shadow period (April 20 - June 12):

- S-RAD correctly anticipated **15% of sexual assaults** occurring on Los Angeles UberX trips (13/85) at the 1% trip trigger rate. This included **38% of L4 sexual assaults** (3/8).
- 99% of trips flagged by the model (at the 1% trip trigger rate) had an alternative driver-rider match that passed the model check (i.e., scored under risk threshold).
- Female and male drivers are not flagged at a different rate.

Predictive Performance

Figure 8 depicts the recall-trigger rate curve for shadow mode predictions for Los Angeles UberX trips. At the 1% trip trigger rate, the model predicts 15% of sexual assaults, including 38% of L4 sexual assaults. If the model were calibrated at the 0.5% trip trigger rate, the model would have flagged ~8% of L3/L4 sexual assaults.

Importantly, however, prediction does not equal prevention. Because prevention requires down-ranking to effectively block driver-rider matches with elevated risk, there needs to exist alternative driver-rider matches for the flagged pair that are scored as low risk. This may not be possible when there is a shortage of supply, or if the model tends to flag all potential dispatches for a rider's request as risky (e.g., if rider features in the model dominate predictions).

Randomized experiments will ultimately be necessary to address these concerns in a compelling way, but as a first step we can examine if trips that were flagged in shadow (positives) had alternative driver-rider pairings that were considered for dispatch and passed the model check (e.g., had a risk score under the threshold for down-ranking). Furthermore, we can examine what the potential change in ETA and risk score would have been by dispatching the next best driver.

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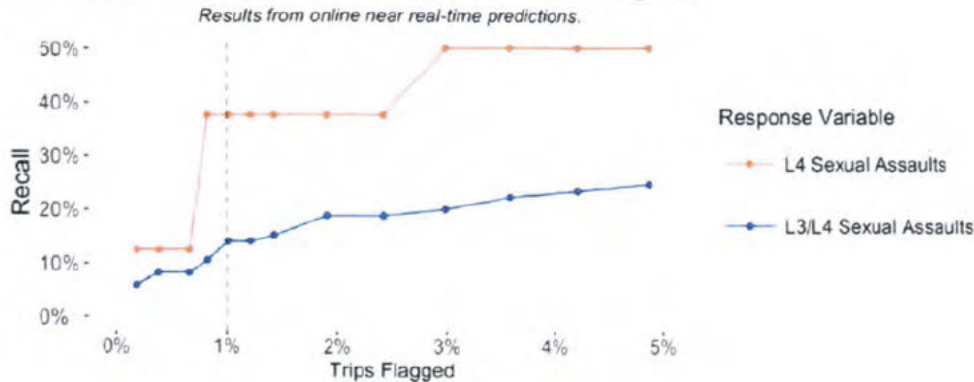
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Figure 8

S-RAD Shadow Mode Performance in Los Angeles



Notes: Los Angeles UberX trips between April 20 - June 12, 2018. Recall for all sexual assaults with both driver + rider reporters (source: JIRA). 65 L3/L4 incidents and 8 L4 incidents. Results from V0 Combined Gender Model.

Table 4: Next Best Unflagged Match for Flagged Trips (LA Shadow; UberX Only)

	Flagged Trips with Incidents	Flagged Trips
Trips	13	5000
Trips with Alternative Match	92% (12/13)	>99% (4986/5000)
Median Change in ETA* (mean in parentheses)	+12 secs (+72 secs)	+32 secs (+52 secs)
Median Change in Model Risk Score* (mean in parentheses)	-0.11 (-0.20)	-0.13 (-0.20)

Notes: Model calibrated at the 1% trip trigger rate. Sample consists of all 13 sexual assaults correctly flagged (true positives) during April 20 - June 12, and a random sample of 5k flagged trips (positives) during June 1 - 7.

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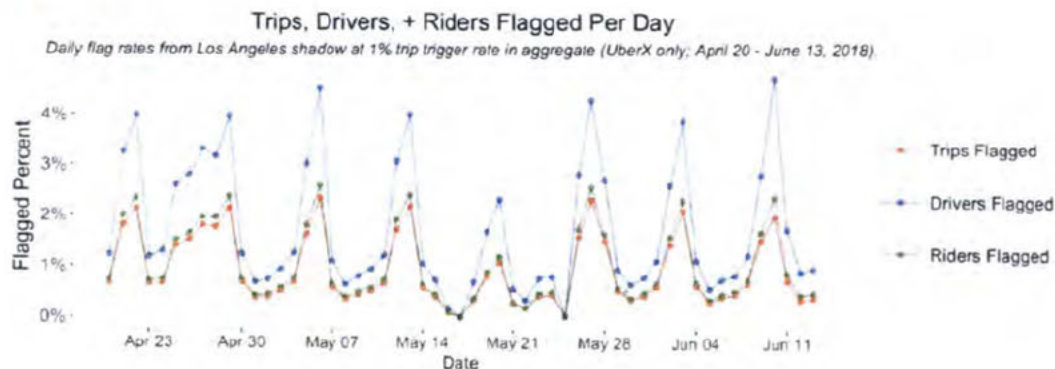
To generate these insights, two types of positives are sampled: all 13 true positives (flagged trips with incidents), 5k randomly selected positives (flagged trips). For each of these trips, we collect all driver-rider pairings considered for that trip request (according to rawdata.kafka_hp_multileg_mgv_log_nodedup), score the risks associated with the pairings, and examine the percent of trips with an alternative driver-rider pairing that passed the model check. Results are presented in [Table 4](#), and show that 92% of true positives and 99% of positives had alternative driver-rider pairings that passed the model check. If the driver with the lowest ETA amongst all drivers passing the model check were dispatched, the median change in ETA is +12 seconds for true positives and +32 seconds for positives. **Note, however, that this analysis does not solve the global dispatch optimization problem used in production, so these high-level estimates need to be re-assessed via rigorous online experiments.**

Flag Rates at 1% Trip Trigger Rate

During the shadow mode period, there were ~500k UberX trips per day in Los Angeles. A 1% trip trigger rate thus equates to approximately ~5k down-ranked trips per day. However, because safety risks vary by time and space, flag rates can vary significantly depending on the unit of analysis (e.g., day-level, hour-level, hexagon-level).

[Figure 9](#), for example, shows that at the 1% trip trigger rate calibration in the aggregate, the daily trip trigger rate fluctuates between 0.01% to 2.35% (<25 trips flagged per day to >15k trips flagged per day). On the average, 1.74% of drivers and 1.02% of riders taking trips are impacted each day.

Figure 9



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Another way of assessing the potential marketplace costs is to examine the percent of **driver-rider pairs** flagged, where driver-rider pairs are comprised of all driver-rider pairs considered for an UberX request (not just those culminating into a trip).

At the 1% trip trigger rate, approximately 1.26% of all driver-rider pairings considered for dispatch are flagged for down-ranking each day on the average, with the highest flag rates occurring on the highest risk days (e.g., >3% on weekends). These flag rates are presented in [Figure 10](#).

The rate at which driver-rider pairs are flagged also increase significantly on weekends between 12-3am -- the time of the day when the sexual assault incident rate is highest (see [Appendix Figure A.1](#)).

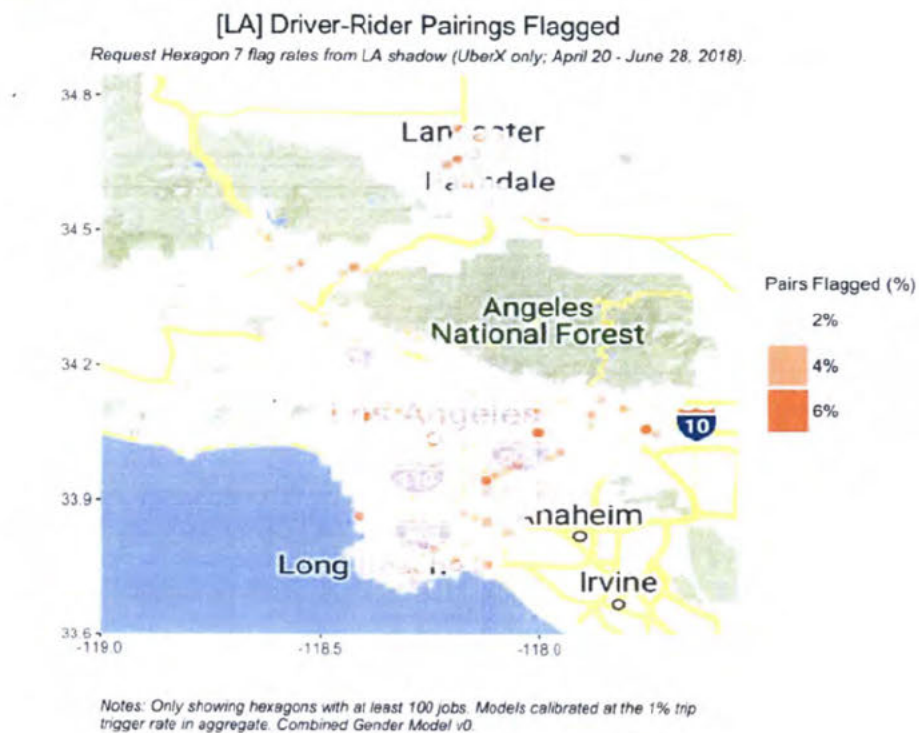
Finally, [Figure 12](#) illustrates the distribution of flag rates across space (at the hexagon 7 level, with each hexagon 7 being approximately 5.16 km² in size). On the average, 1.22% of driver-rider pairs are flagged across each hexagon 7, with the highest flag rate being 6.35%.

Figure 10



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Figure 12



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6. Implementation Plan [\[back to top\]](#)

Because S-RAD is likely to have a meaningful impact on both safety and the marketplace, a rigorous evaluation needs to be conducted in stages. The evaluation must demonstrate that:

- Sexual assaults can be better anticipated (prediction).
- Down-ranking based on model predictions can reduce the incident rate (prevention).
- Down-ranking can be achieved within marketplace constraints (business).
- Down-ranking does not have a disproportionate impact on driver earnings or ATAs by gender (legal).

To answer these questions, the *proposed* evaluation plan consists of a limited pilot, a within-city switchback, and a multi-city experiment (pending discussions with Operations, Marketplace, Legal). The full details of the evaluation plan is available in this document: [S-RAD Evaluation Plan](#). A high-level roadmap is provided in Table 5 below.

Table 5. Proposed 2018 Roadmap (Pending Stakeholder Reviews)

	JUL	AUG	SEP	OCT	NOV	DEC
Shadow Deployments Select US Cities						
Evaluation #1: Blue-Red Experiment						
Review #1 with Stakeholders RGM/GMs, Operations, Safety Leadership, Legal, Marketplace.						
Evaluation #2: Within-City Switchback (Los Angeles)						
Review #2 with Stakeholders RGM/GMs, Operations, Safety Leadership, Legal, Marketplace.						
Evaluation #3: City-Level Randomized Experiment (DID) N US cities (to be selected with ops + marketplace)						
Review #3 with Stakeholders RGM/GMs, Operations, Safety Leadership, Legal, Marketplace.						
Scale (pending evaluation results)						

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****Precise timelines depend on experiment results (meet acceptance criteria) and stakeholder reviews.*

7. Team [\[back to top\]](#)

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Appendix A: Descriptive Statistics [\[back to top\]](#)

Figure A.1

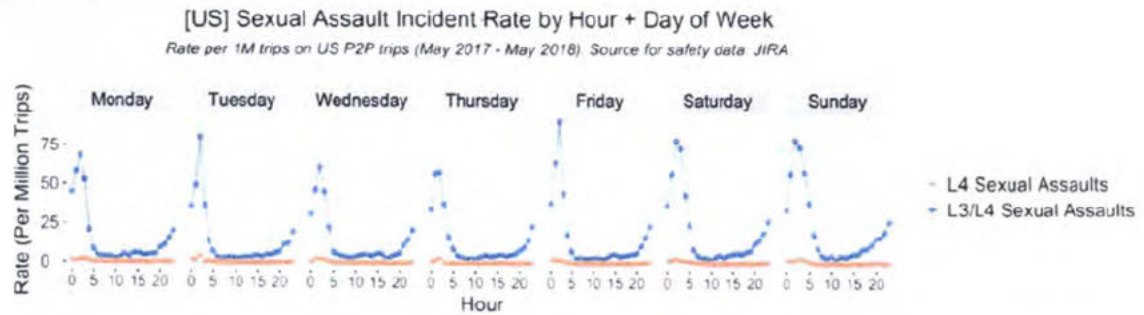
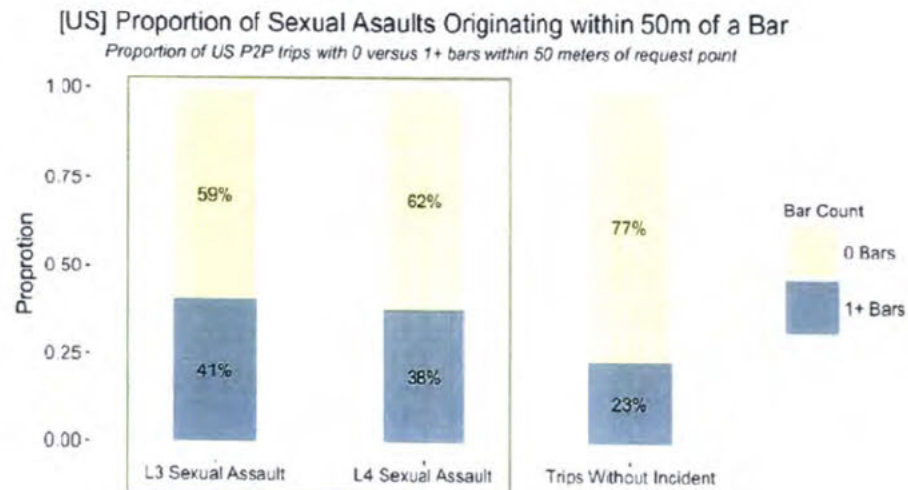


Figure A.2



Notes: 100% sample of sexual assaults (13555 L3 sexual assaults, 382 L4 sexual assaults) and 250k randomly selected trips without sexual assaults (source: JIRA). US P2P occurring March 1 - May 14, 2018.

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Figure A.3

Problem for Females and Males

Female Users		Male Users	
Top 5 Most Common Safety Incident Types		Top 5 Most Common Safety Incident Types	
Incident Category	Proportion Of Cases	Incident Category	Proportion Of Cases
1. Accident or Claim	52%	1. Accident or Claim	50%
2. Sexual Assault	22%	2. Physical Altercation	25%
3. Physical Altercation	10%	3. Sexual Assault	12%
4. Sexual Misconduct	6%	4. Verbal Altercation	3%
5. Substance Abuse	2%	5. Health / Self-Harm	3%

Notes: Data divided by "gender of alleged victim" (inferred gender based on first name). JIRA data only. Incidents from US P2P trips only (May 2017 - May 2018). Excluding Law Enforcement/Regulatory.

Figure A.4

Sexual Assault Incident Rate by Gender of Driver + Rider

US P2P incidents occurring May 2017 - May 2018

	Female Drivers		Male Drivers	
	+ Female Rider	+ Male Rider	+ Female Rider	+ Male Rider
Rate of Sexual Assaults (Per 1M Trips)	8.36	38.98	13.10	7.93
Num of Sexual Assaults	549	3114	5476	4014
Num of Trips	66M	80M	418M	506M

Notes: Only US P2P trips and incidents occurring May 2017 - May 2018 with inferred gender data (97% coverage in sample). Safety data source: JIRA.

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Figure A.5

Gender of Alleged Offender of Sexual Assaults

US P2P incidents occurring May 2017 - May 2018

	Gender of Alleged Offender	
	Female	Male
L3 Sexual Assaults (13,342 cases)	14%	86%
L4 Sexual Assaults (371 cases)	4%	96%

Notes: JIRA sexual assault tickets from US P2P trips occurring May 2017 - May 2018. Includes only sexual assaults with inferred gender data (97% of incidents) and those where the alleged offender is the driver or rider (73% of incidents).

Table A.1: Sexual Assault Incident Rate in 2017 by US Sub-Region

US Sub-Region	Sexual Assault Incident Rate (Per 1M Trips)	Sexual Assault Incident Count	Trip Count
South	19.60	1723	87890588
Southwest	15.24	2695	176791541
Midwest	14.30	1779	124389720
Southeast	13.43	3319	247075343
Pacific Northwest	12.69	365	28760375
NorCal	10.17	944	92785270
Caribbean & Panama	9.64	24	2489858
New England	9.12	525	57588019
TRIPAD	8.48	1761	207577926

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Table A.2: Top 10 Cities with Highest Sexual Assault Incident Rate in 2017
(Amongst Large Cities w >20M Trips)

City	Sexual Assault Incident Rate (Per 1M Trips)	Sexual Assault Incident Count	Trip Count
Atlanta	13.56	420	30983618
Los Angeles	13.32	1251	93932481
Miami	11.34	638	56256087
Philadelphia	9.97	278	27892521
Chicago	8.92	631	70724834
San Francisco	8.85	753	85055360
New Jersey	8.59	356	41442850
Boston	7.97	393	49285208
Washington D.C.	7.79	494	63401431
New York City	6.16	671	108851902

Table A.3: Top 10 Cities with Highest Sexual Assault Incident Rate in 2017
(Amongst Medium-Sized Cities w <=20M Trips but >1M Trips)

City	Sexual Assault Incident Rate (Per 1M Trips)	Sexual Assault Incident Count	Trip Count
Albuquerque	45.18	51	1128833
Pensacola, FL	41.63	42	1008853
El Paso	37.25	38	1020003
Wilmington, NC	36.67	39	1063595
Oklahoma City	32.39	54	1667435
Omaha	32.35	36	1112946
Fresno	31.52	41	1300872
Fort Myers-Naples	29.03	54	1859865
Central Atlantic Coast, FL	28.66	43	1500494
Kansas City	28.08	105	3738970

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Table A.4: Top 10 Cities with Highest Sexual Assault Incident Rate in 2017
(Amongst Small Cities w <=1M Trips)

City	Sexual Assault Incident Rate (Per 1M Trips)	Sexual Assault Incident Count	Trip Count
Juneau	103.52	1	9660
Jonesboro	100.21	1	9979
Bowling Green, KY	92.68	7	75531
Topeka	91.43	6	65626
Tri-Cities	80.00	4	50000
Sioux City	73.74	2	27121
Green Bay	66.42	28	421590
Stillwater	64.92	7	107823
Tri-Cities, MI	63.19	3	47476
Huntsville, AL	61.04	10	163817

Appendix B: Variable List + Definitions [\[back to top\]](#)



Appendix C: Evaluation Plan [\[back to top\]](#)



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